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## Jan Barilla Selection of rubbing trees by brown bears in Slovakia



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This thesis is worth 60 study points

### Abstract

Chemical communication in bears is not fully understood, despite the importance of this topic for the behavioral ecology as well as for the conservation and management of Ursids. Brown bears often mark trees by rubbing on them as well as biting and clawing of the bark. Such rubbing trees are often used for the collection of hair samples for genetic analyses needed for management purposes. The aim of this study was to document rubbing trees in the eastern part of Tatra National Park, Slovakia, and to create a predictive habitat model to guide searches for rub trees in other parts of Slovakia. We created a grid system of 100 random transects in a 140km<sup>2</sup> study area, and walked the trails and random transects in search for rub trees from March to October 2015-2017. For each rub tree we recorded its location in the landscape, the habitat type surrounding it, as well as several variables describing the tree itself. We documented 85 rub trees in the protected area Belianske Tatry. These trees were significantly more often located along trails in comparison to random transects, however, bears also seemed to prefer less human-frequented (i.e., seasonally closed) trails. Bears significantly preferred coniferous tree species: Norway spruce and European larch with a trunk diameter larger than the mean trunk diameter of trees in its vicinity. We created a predictive model for rubbing trees using Maximum Entropy modelling (MaxEnt), based on only-presence data of rub trees and 9 environmental variables. The final model are 100 replicates of MaxEnt algorithm with random seed of training samples resulted in an average training Area under curve (AUC) value of AUC value of  $0.941 \pm 0.012$ . This model could help to simplify design of genetic studies for monitoring of population and studies about rubbing behavior of brown bears in the Tatra National Park and other areas in Slovakia. But it will also provide insight in the chemical communication of bears.

Key words: Brown bear, ursus arctos, rub tree, Maximum Entropy modelling, MaxEnt

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Bø i Telemark, 15.5.2018 Jan Barilla

### **1. Introduction**

Communication in mammals is based on visual, acoustic and chemical signals (McGregor, 2005). Olfactory communication has been defined as the process whereby a chemical signal is generated by a presumptive sender and transmitted (generally through the air) to a presumptive receiver whoby means of adequate receptors can identify, integrate, and respond (either behaviorally or physiologically) to the signal (Eisenberg and Kleiman, 1972). Together with odor signals is common among mammals and has the advantage that signals are long lasting and are also transferred in the absence of the sender individual. (Eisenberg and Kleiman, 1972). Olfactorial signals carry information about the individual, its age and/or reproductive status, and are commonly used to reduce aggressive encounters as well as in marking home ranges or territories (Rosell and Thomsen, 2006). To produce chemical signals in mammals, different glands are described. Examples are supracaudal gland, which is known from foxes (vulpes vulpes) (Albone and Flood, 1976) and anal glands secretion (AGS), known from giant pandas (Ailuropoda melanoleuca) (Nie et al., 2012). Also brown bears (Ursus arctos) possess glands, such as anal sacs and pedal glands. Anal glands produce AGS independently from feaces (Rosell et al., 2011). It is experimentally proofed, that AGS by brown bears can be used for sexual discrimination (Jojola et al., 2012). Finding of pedal glands supports the existence of chemical communication through pedal marking in brown bears (Sergiel et al., 2017). In mammals, the principal function is to limit the energetic costs of producing scent marks by placing marks to strategic places, where is higher likelihood of attracting potential receivers (Clapham et al., 2013). Tree rubbing by bears has been observed throughout the northern hemisphere (Green and Mattson, 2003). Bear rub trees were often observed along bear trails (Servodkin, 2014, Burst and Pelton, 1983) and were identified as part of intraspecific communication (Tschanz et al., 1970). Bears chose trees or other object to depose their scent marks. Together with damage on the marking object is combination of visual and odor signal (Clapham et al., 2013, Karamanlidis et al., 2010). The intraspecific communication in bears is not totally understood and more research is needed (Rijáková, 2015). In a Canadian brown bear population, scent marking behavior was most frequent by adult males during the mating season. Despite the female bears are probably not marking their estrous status (Clapham et al., 2012, Clapham et al., 2014). Research of different brown bear population showed that the bears do not seem to randomly select tree for marking. Several studies have shown that bears seem to prefer coniferous trees for marking (Clapham et al., 2013, Sato et al., 2014, Tattoni et al., 2015). The preference of some tree species is likely related to the chemical composition of these species (Kimball et al., 1998). Bears usually also prefer to rub on relatively large trees (Green and Mattson, 2003, Clapham et al., 2013, Sato et al., 2014). Repeatedly rubbing on the same trees by brown bears was recorded within a year and across multiple years (Sato et al., 2014). Bears sometimes also additionally mark on trees with biting and clawing, but rubbing is the most frequently observed behavior (Green and Mattson, 2003). Bears have been observed to rub their body with horizontal or vertical movements against trees. Their postures can be bipedal, quadrupedal, sitting or even lying down (Clapham et al., 2014). At the landscape level, grizzly bears selected for gentle southfacing slopes, forest/non-forest ecotones with sparse deadfall, and forest stands dominated by pines (Green and Mattson, 2003). The location of rub trees was described on human made or game trails, mountain ridges or valley bottoms (Clapham et al., 2013). Bear rub trees are a natural source of bear hairs commonly used for non-invasive sampling in many genetic population studies (Woods et al., 1999, Kendall et al., 2008, Sawaya et al., 2012). Understanding the distribution of such rub trees across the landscape would be useful for population management and population monitoring purposes. Distribution modeling is useful tool for wildlife management. There is as well a model of multi-scale resource selection function for bear rubs in northwestern Montana (Morgan Henderson et al., 2015). Distribution model of rub trees was based on following covariates: elevation, open-road density, slope steepness and distance to greenness. This model supports the use of rub trees as a source of genetic material for population monitoring studies.

Maximum Entropy Modeling (MaxEnt) is widely used method of distribution modeling with very good predictive accuracy (Elith et al., 2011). It is suitable tool for bear habitat modeling with many different environmental variables described. Distances to forest edges, trails, roads and settlements were 4 out of 9 variables used in Italian study (Adjaye, 2011). Slope aspect, vegetation cover types and 19 other variables were tested in other Italian study (van Gils et al., 2014). Based on literature we looked for possible data layers of our study area to model rub tree distribution.

The main goal of this research project was to create a predictive model for the presence of bear rub trees in the Tatra National Park, Slovakia. I used MaxEnt modelling to investigate the following research question: Does forest type, average age of forest patch, elevation above sea level, distance to roads, distance to forestry trails, distance to edge of forest patches, distance to settlements, slope and slope orientation affect the distribution of bear rub trees? I investigated to following null nypothesis : Forest type, average age of forest patch, elevation above sea level, distance to roads, distance to forestry trails, distance to edge of forest patch, distance to settlements, slope and slope orientation do not affect the distribution of bear rubbing trees in Tatra National Park, Slovakia.

### 2. Materials and Methods

#### 1.1. Study area

The study area was in Belianske Tatry Mountains (located at  $49^{\circ}14'25.6"N$   $20^{\circ}13'11.7"E$ ), which is part of the Tatra National Park (TANAP) in Slovakia (Figure 1). The size of the study area was  $140 \text{ km}^2$  and included parts of surrounding mountain ranges (High Tatra Mts, Magura Mts). The large range in elevation from 756 m to 2479 m causes variability in climatic conditions. Depending on the location, the average precipitation is 1100 - 1600 mm, snow cover lasts from November until May, and the length of the growing season in the forested areas is approximately 70 - 100 days. About 71% of the study area is covered by forest, of which more than 60% are strictly protected. The rest is managed forests with a developed network of forestry roads and hiking trails (~74.3 km).



*Figure 1: Location of study area (in yellow) in the Tatra National Park, Slovakia. The blue line indicates the border with Poland.* 

Three main settlements, Ždiar (896m a.s.l.), Tatranská Javorina (1018m a.s.l.) and Tatranská Kotlina (760m a.s.l.), are located at lower elevations. The foothill zone up to 800 m a.s.l. is covered with managed spruce (*Picea abies*) forests occasionally intermixed with deciduous species, such as European beech (*Fagus sylvatica*), sycamore (*Acer pseudoplatanus*), and European ash (*Fraxinus excelsior*). The montane zone ranges from approximately 800 to the tree line at 1380 m a.s.l. and typically consists of coniferous species, such as spruce, silver fir (*Abies alba*), Scots pine (*Pinus sylvestris*), and European larch (*Larix decidua*) as well as deciduous species such as European white birch (*Betula pendula*), grey alder (*Alnus incana*), rowan (*Sorbus aucuparia*), and willows (*Salix spp*). Above the tree line is the subalpine zone up to 1800m a.s.l. with patches of scrub mountain pine (*Pinus mugo*). The bear population density in the Tatra National Park is estimated at 7 individuals per 100 km<sup>2</sup> (Lenko et al., 2014, Barilla, 2015).

#### **1.2.** Data collection

The fieldwork was carried out from March to October in 2015-2017 (Figure 2). I created two data sets for the analysis of my research questions. Data set 1 consisted of data on tree as well as habitat characteristics at random locations. Data set 2 consisted of tree and habitat characteristics at bear rub trees. To create data set 1, I randomly selected 100 locations with the ArcGIS random selection function in the forested part of the study area. The coordinates of these 100 random locations were imported into a handheld GPS device (Garmin eTrex 40) and each of the locations was visited. At each random location I recorded the following characteristics of the tree closest to the random location (see Random tree protocol in Appendix 1): tree species, diameter at chest height, height, presence of a trail.

To create data set 2, I systematically searched for bear rub trees along forestry roads, forestry trails, hiking trails and in 25 x 25 m plots around the random locations.



Figure 2: Study area in the Tatra National Park, Slovakia, with the distribution of 100 random locations (yellow dots), recorded rub trees (red dots), and GPS track log (yellow lines) of the search for bear rub trees along roads and trails.

A bear rub tree was defined as a tree with bear hair present and bark that was visible worn by bears with rubbing, scratching, or biting (Seryodkin, 2014). In addition, often bite and/or claw marks were visible as indication for brown bear rubbing behavior (Figure 3). At every rub tree I recorded the following tree characteristics: tree species, diameter at chest height, height, presence of a trail and grade of marking. For more details, see the protocol in Appendix 2. In addition, I recorded the same characteristics of a randomly selected tree within a radius of 30 meters around each rub tree. I selected a random tree based on a list of random angels (0°-360°) and random distances (0-30m) generated with the random function in Miscrosoft Excel® before visiting the field.



Figure 3: Bear rub tree with bite marks in the Tatra National Park, Slovakia. The inserted picture shows a close up of bear hairs present in the worn area on the tree trunk.

#### **1.3.** Environmental variables

Based on the existing literature (Koreň et al., 2011, van Gils et al., 2014, Sánchez, 2013, Green and Mattson, 2003, Morgan Henderson et al., 2015), I selected 9 environmental variables to characterize the presence or absence of bear rub trees on the landscape scale: Distance to road, Forest type, Average age of forest patch, Slope aspect, Distance to forestry trails (as defined by the Slovakian Forestry Inventory), Slope steepness, Distance to settlements, Elevation above sea level, and Distance to edge of the forest patch. I used raster and vector data from the 'National Forest Centre' (© NLC Zvolen, 2016) to extract these environmental variables from a 25x25 m grid in all grid cells with random locations and in all grid cells with bear rub trees with ArcGis® version 10.1. Tree species composition was derived in the Forest type. The forest type as well as the forest age in each grid cell were categorical variables using the forest type categories as defined by the Slovakian Forestry Inventory (© NLC Zvolen, 2016). Forest site

classification on the national scale consists of 365 forest types. Forest types with similar characteristics were combined into 92 categories of the forest types (Koreň et al., 2011). I used the 'Euclidean Distance' function in ArcGis 10.1 and vector layers of forest stand maps and forestry trail maps to calculate distances between grid cells with random locations or bear rub trees to the nearest trail or forest edge. A digital elevation model (DEM) with resolution of 1:25 000 was used to extract the variables elevation above sea level, slope and slope orientation in ArcGis 10.1. Distances to settlements, buildings and roads were rasterized from OpenStreetMap® (www.openstreetmap.org) and calculated with the 'Euclidean Distance' function in ArcGis.

#### **1.4.** Statistical analysis

Parametric and non-parametric statistics were used to evaluate and compare characteristics of bear rub trees. Statistical significance was set at  $P \le 0.05$ , and the statistical software Minitab 11 was used in this analysis.

#### 1.5. MaxEnt Modelling

I used species distribution modeling (SDM) to create a predictive model of bear rub trees distribution across TANAP. Maximum Entropy modelling (MaxEnt) is a commonly used method for presence-only data with low sample sizes. MaxEnt achieved best results out of 16 methods in the comparison study with independent presenceabsence data (Elith et al., 2006). MaxEnt estimates the probability of occurrence of bear rub trees across the landscape based on environmental variables. All raster layers of environmental variables were converted with ArcGis 10.1 into '.aci' format required for MaxEnt following instructions (Young et al., 2011). Maxent software, version 3.3. 3 was used for further analysis (Philips et al., 2010).

I used 25% of the samples for training of the algorithm, and 75% for developing a predictive model of bear rub tree presence in TANAP. Common method to evaluate the accuracy of predictive models logistic regression of sensitivity versus specificity. Two indices are used a test that predicts dichotomous outcomes. They describe how well a test discriminates between cases with and without a certain condition.

Sensitivity - the proportion of true positives or the proportion of cases correctly identified by the test as meeting a certain condition. Specificity is the proportion of true negatives or the proportion of cases correctly identified by the test as not meeting a certain condition (Roos et al., 1996). Spatial overlay of predicted presence/absence with raw data collected in the field was used to calculate the average training area under the curve (AUC). AUC as well as the receiver operating characteristic (ROC) curve is calculated as function of specificity versus sensitivity (Elith et al., 2011, Roos et al., 1997).

For model evaluation, the false positive rate known from presence/absence modeling Fractional Predicted Area was used. The Fractional Predicted Area in MaxEnt estimates the fraction of background cells for which is presence predicted. To see model performance there average sensitivity versus specificity calculated and displayed with AUC curve. By the interpretation is important that our method is based only on the presence data (Elith et al., 2011). To estimate the contribution of each variable to the modelling results, I used a Jacknife procedure that removes a variable from the analysis, re-calculates model estimates, and then compares model estimates with and without the presence of a given variable (Phillips, 2005). The environmental variable that reduces the gain most when excluded has the most informativeness (Adjaye, 2011).

### **3. Results**

#### **1.6.** General results

An overall sample of 79 bear rub trees was identified. About 86% of the rub trees also had bite or claw marks. Bears preferred to rub significantly more often on spruce trees compared to other tree species (Chi-Square Goodness-of-Fit Test, N = 79,  $\chi^2$  = 71.203, df = 1, P ≤ 0.001). Only 2 of 79 rubs were on larch trees. The proportion of random tree species was 88.6% needle trees (spruce: 82.3%, larch: 2.5%, fir: 1.3%, dwarf pine 2.5%) and 11.4% deciduous trees (sycamore: 3.8%, rowan: 2.5%, beech: 1.3%, alder: 3.8%). Bears also selected for rub trees with a significantly larger diameter compared to random trees (mean diameter rub tree: 27.56 ± 11.21 cm (SD), mean diameter random tree 20.16 ± 14.68 cm; paired t-test, N = 79, T = 3.83, P ≤ 0.001). Bear rub trees occurred significantly more often than expected near forestry trails (Chi-Square Goodness-of-Fit Test, N = 79,  $\chi^2$  = 74.671, df = 3, P ≤ 0.001) in comparison to game trails (25%), forestry roads (4%) and hiking trails (6%).

#### 1.7. MaxEnt modelling results

After removal of duplicates of rub tree presence records in the same grid cell, 82 grid cells with at least one bear rub tree present were used in the MaxEnt modelling procedure. Model evaluation plots suggested that modelling results and predictions obtained were robust and fulfilled all requirements (Appendix 3 and 4). I calculated 100 replicates with the training data set, which resulted in an average training AUC value of  $0.941 \pm 0.012$  (Appendix 3). The MaxEnt modelling procedure suggested that the variables 'distance to road', 'forest type', and 'average age of forest patch' were most important in explaining the location of rub trees in the study area (Table 1).

Table 1: Environmental variables used to evaluate the presence of bear rub trees in Tatra National Park, Slovakia. Variable is the variable name, values describes the value range of a specific variable, contribution is the proportional contribution of a variable to the overall model, and importance describes the proportional permutation importance of a variable in the MaxEnt model.

Variable	Value	Contribution (%)	Importance (%)
Distance to road	0 - 3812 m	31.1	16.3
Forest type	categorical: 29	18.2	17.4
Average age of forest patch	1 - 210 yrs categorical: 49	17.8	12.7
Slope aspect	categorical: 9	9.5	7.2
Distance to forestry trails	0 - 2775 m	6.9	14.6
Slope steepness	0 – 76.8 deg	5.2	7.6
Distance to settlements	0 - 4534 m	6.5	17.3
Elevation above sea level	756 - 2479 m	3.8	5.5
Distance to edge of forest patch	0 - 2665 m	1.1	1.5

The results of the average values over 100 replicates are shown in the figure 4. Replicates are multiple runs of model with new random selection for test samples (Phillips, 2005). The jackknife procedure supported that the most important variables in the analysis were distance to roads, distance to forestry trails, average age of forest patch, forest type, and elevation above sea level. Distance to roads is the environmental variable that decreased the explanatory power of the model the most when omitted, which suggests that it is the most informative variable.



Figure 4: The results of the jackknife test of variable importance, using test gain, training gain and are under the curve (AUC) on test data. The x-axis represents the predicted probability of bear rub tree presence in relation to a given environmental variable.

Response curves for each environmental variable show how the logistic prediction changes if exatly one environmental variable is changing (Figure 5). The model may take advantage of sets of variables changing together (Phillips, 2005). The response curves

show the marginal effect of using only one corresponding variable and dependencies induced by correlations between the selected variable and other variables displayed in probability. These plots reflect the dependence of predicted probability. The Y-axis shows the predicted probability of bear rub tree presence in relation to a given environmental variable. Note that extensions of curves below zero is a default setting of the MaxEnt algorithm that cannot be changed.



Figure 5: Response curves of the continuous variables. Each of the following curves (red) and the mean +/- one standard deviation (blue) represents a different MaxEnt model created using only the corresponding variable. Y-axis is predicted probability of environmental conditions suitable for brown bear rubbing behavior.

The probability for the presence of bear rub trees increased with increasing elevation up to the tree line at about 1800 m, after which it sharply declined. Further, the highest probability for bear rub tress was at medium to steep slopes. The probability for the presence of rub trees was highest in the distance of first couple hundred meters to forestry trails but decreased with increasing distance from forestry trails, and also decreased with increasing distance from the edge of forest patches as well as forestry roads. About 48% of rub trees (N:85) were located at the edge of a forest patch. The maximum distance of a rub tree to the nearest forest edge was 112 m. The average distance of a rub tree from a forestry road was  $468 \pm 350$  m, and the maximum distance was 3300m. The probability of rub tree occurrence increased with increasing distance from settlements and was highest at 3750 m from settlements, after which it decreased again.

In the figure 6 are plots of models with only the corresponding categorical variable. Only 29 categories of different forest type's were identified in our study area. In all preferred forest categories is spruce contributed. The highest probability for bear rub tree presence was in forest patches of age 165 years and 175 years, but generally highest in either very old or relatively young stands, and lowest in medium-aged stands. The highest probability for the occurrence of bear rub trees was on slopes oriented to the southwest, west and northwest (Figure 6).



Figure 6: Model plots of corresponding categorical variables used to predict the presence of bear rub trees in Tatra National Park, Slovakia. The mean response for every categorical variable of the MaxEnt is presented in run (red) and the mean +/- one standard deviation in blue. The Y-axis represents the predicted probability of presence of bear rub trees in relation to environmental variables.

The final predictive model for bear rub tree presence in TANAP is presented in Figure 7. Red predicts areas with the highest probability for brown bear rubbing trees, while dark blue predicts areas with very low probability of occurrence.



Figure 7: Predictive model for bear rub tree presence in Tatra National Park, Slovakia. Red predicts areas with the highest probability for brown bear rubbing trees, while dark blue predicts areas with very low probability of occurrence. Black are areas with no forest coverage.

### 4. Discussion

The selected environmental variables do affect the distribution of bear rubbing trees. The overall model performed very well with an excellent average training AUC value of  $0.941 \pm 0.012$  (for more details see Appendix 3). AUC value above 0.877 means that model fits very good to data (Roos et al., 1996). The environmental variable were evaluated (see Results, table 1). Distance to road, Forest type and Average age of forest patch were the most informative. They inform about habitat characteristics and human disturbance through distance to the roads.

In a study, they calculated probability of brown bear occurrence, Adjaye (Adjaye, 2011) described the increasing probability of occurrence with increasing elevation in the Italian Alps. I found a similar pattern for the occurrence of bear rub trees in the Slovakian Tatra Mountain, i.e., the probability of rub tree occurrence increased with increasing elevation. However, by definition, the occurrence of rub trees stopped at the tree line, which resulted in a bell-shaped occurrence response (see chapter results, figure 5). The bears in Sweden had a higher probability of occurrence the further away from people it was and the more rugged (i.e., steeper and more mountainous) the area was. (Nellemann et al., 2007)

Bear rub trees occurred also more often at steeper slopes up to 30°. In comparison, a study in Montana, USA, showed decreasing probability of bear rubs with increasing slope steepness (Morgan Henderson et al., 2015). However, the study area TANAP is a relatively small a very mountainous, and more intense human use may occur in less steep slopes.

In this study, I found that bears prefer to rub along the human made trails, where are no vehicles passing. (Morgan Henderson et al., 2015) found no difference in the selection of bears for rub tree locations along trails or roads. In comparison, Tattoni et al. (Tattoni et al., 2015) found a negative effect of passing cars on bear rubbing behavior in Italy. This different could indicate behavioral differences in different brown bear populations may be explained by behavioral plasticity (Clapham et al., 2013).

To calculate probability of occurrence of European brown bear, distance to roads was used (Adjaye, 2011). According (Mueller et al., 2004) findings, subadult bears are using habitat closer to roads as adult bears. Highest frequency of rubbing behavior by adult male bears were recognized in several studies (Clapham et al., 2013, Karamanlidis et al., 2010). Distance from roads was variable with the highest contribution in our model, it may indicate higher roads density and higher human pressure with less suitable habitats for rubbing behavior.

The edge effect was used in contribution with other variables for brown bear habitat suitability model in Spain (Sánchez, 2013). In Italy, the probability of brown bear occurrence decreased with increasing distance from the forest edge (Adjaye, 2011). A similar trend was also described for bear rub trees in Yellowstone National Park USA (Green and Mattson, 2003). The contribution of the variable distance to forest edge was comparatively modest in the MaxEnt modelling results, however, this is likely related to correlations with other variables, especially with the variable presence of forestry trails, because such trails are often located the edges of the forest patch.

The probability of rub tree occurrence increased with increasing distance from buildings and settlements, which is similar to results found in Italy (Tattoni et al., 2015). The highest probability of occurrence of bear rub trees in TANAP was at 3750 m from settlements but decreased afterwards again. This is likely related to the presence of the timberline, where the probability of rub tree occurrence by definition must decrease.

In Sweden, middle old and old forest are preferred habitats for rub tree occurrence (Dathe, 2008). The highest occurrence probability for rub trees in our study was in either very old or relatively young stands, and lowest in medium-aged stands. Approximately 8% of the rub trees occurred in a natural tree fall areas due to a big storm in 2004 (Némethy et al., 2018). These windfalls caused big changes in old spruce forests in the habitat of bears in TANAP. Many old forest were reclassified to young stands, this change cloud cause more rubs in relatively young stands.

Bears rubbed almost exclusively on spruce trees in TANAP. The preference of bears for coniferous trees in commonly observed (Rijáková, 2015, Puchkovskiy, 2009, Green and Mattson, 2003), and (Sato et al., 2014) suggested a possible multimodal signal amplification of bear chemical signals due to the natural resin of coniferous trees.

Most bear rub trees in TANAP occurred on slopes with southwest, west and northwest exposure. Bears in the Italian Alps choose more often southwest, northeast, southeast facing slopes for tree rubbing (Tattoni et al., 2015). I speculate that this may be related to the prevalent northwest wind direction in TANAP, which would support better spread of the scent on preferred slopes and bigger chances for a receiver to obtain the information.

Rub trees are not randomly distributed across the landscape. (Clapham et al., 2013) speculated that the occurrence of brown bear rub trees may be related to the movements and use of trails as migration corridors. In several North American and European countries, natural bear rubs rare used for the genetic population monitoring of brown bears (Kendall et al., 2008, Sawaya et al., 2012, Karamanlidis et al., 2012)We suggest that our model could be used to create new sampling method, using rub trees for genetic monitoring of brown bears in Slovakia. The hair traps could be placed at rub tree locations to collect samples for genetic analyses, thereby gaining further insights into bear population ecology. Maybe the predictive model could be expand to more areas to identify rub trees. They could be set up with barbed wire to create system of non-invasive sampling sources for bear population monitoring at national level.

## 5. Conclusion

With the use of MaxEnt modelling I was able to predict locations with bear rub trees with high accuracy. The used environmental variables seem to be sufficient to predict places with high probability of rub tree occurrence. To evaluate our predictions, we would recommend to expand the model to other areas, i.e., the whole Tatra National Park. In addition, further field surveys should be conducted to verify rub tree presence in the field. Ultimately, hair traps could be placed at rub tree locations to collect samples for genetic analyses, thereby gaining further insights into bear population ecology.

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# Appendix

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Appendix 1: Random tree protocol

Random point protocol													
Random poir	nt ID:				Loca	lity:							
Observer:					Date	2:			Time	::			
Location of the tree:	in the fo	rest unit	for	est edge	alpi -lon	ne meadov ie tree	v	meadow - tree	calamity -lone tree				
Species of the	e tree:		Circuit B	H:	cm	Tr	ee height:	r	n	Broken: Yes/No			
Height of the cm	lowest br	anch:	Angle of	tree:		Condition of tree: alive / death							
Trail present: present:	: absent /	hiking/ga	orestry <b>tra</b> i	il forestry machine/gravel/asphalt road									
Bear hairs pr	<b>esent:</b> Yes	/ No	a bear tre 25 x 25m	e within the No / Yes: tree protocol nr:									
Picture of rep	oresentativ	/e place in l	habita	at:	Picture of measured tree:								
Comments:													

### Appendix 2: Rub tree protocol

								Rub t	re	e pro	toc	ol									
Protocol ID:							Locality:														
Observ									Coordinates:			N:									
Date:				Star	rt tim	e:					E:										
Locatio	n of the tr	ee:	fore	est e	dge	in t	n the forest unit			Trail present:				absei	nt	present:				:	
m	eadow-lone	e tre	e		Ca	alamit	nity-lone tree			$\sim$		hikir	ng trail			game trail			forestry trail		
Species	of the tre	e:									for	estr	ry machine road			gravel roa		ad asp		ohalt road	
Picture	of represe	entat	tive h	abita	at:					Positio	ree	rega	rd to s	lope	and trail:		uph	nill	downhill		
Picture	of rub tree	e:								Junctio	n: Ye		es	No		Bend:	Bend: Y		S	No	
Tree he	eight:						m		m	Bite:	pres	sent	nt absent		Cla	w marks:		present		absent	
Conditi	on of tree:		alive death Broken: Yes/No						0	Comments:											
Circuit	BH:		cm Angle of the tree:																		
Height	of the low	est k	oranc	h:				CI	m												
H. of th	he lowest b	oran	ch or	n the	rub	side:		CI	m												
Bear ha	airs presen	t: Ye	s/No	(																	
The hei	ight of hair	s:	Min	.:	C	m M	ax.:	cr	n												
Hair qu	ality:	ne	new		old		both				Present of bear sig						s:				
Resin: absent p		pre	present:		fresh-liquio		id old-hard		ł	carcass			bed		den			turned stone		d stones	
									scat anthills sur						nken footprints foot prints						
										-											
								R	and	ndom tree											
Randor	Random position:			Angle: Dis			stance: m R			Related to the bea			ar tree ID:								
Species of the tree:			C					Co	oordinates:			N:									
Circuit BH:						cm						E:									
Tree height:			m		Angle of tr		tree:	tree: 0		ondition of tree:						alive			death		
Trail present:		- 0	absent		present:			He	Height of the low			st br	anch:		cm						
hiking			game		forestry trail		ail	lt	is a bear	:	No			Yes: bear tree protocol ID:				tocol ID:			
forestry machine			gravel asphalt r			alt roa	ad	Er	nd time:							_					

#### Appendix 3: AUC curve



The AUC curve is resulted in an average training AUC value of  $0.941 \pm 0.012$ . AUC value above 0.877 means that model fits very good to data (Roos et al., 1996). AUC is the average of 100 replicates of MaxEnt algorithm with random seed of training samples.

#### Appendix 4: Omission plot.



Omission rate is a function of cumulative threshold values not to represent real presence. Black curve is predicted omission. Average omission on training data is green curve with yellow standard deviations, which shows variability. Red curve is predicted area as a function of the cumulative threshold with +/- one standard deviation (blue). The mean omission curve is close to the predicted omission, which suggests that the model fits well with the training data.